A Data Analysis Approach of ATR from SAR Images

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1. ABSTRACT

Thales has investigated during these last years a complete target recognition system from SAR images. This paper deals with the specific and original part dedicated to the identification task. Our major contributions are : first, a rational choice of features derived through the use of an image model obtained from data analysis process, and secondly, the use of multiple goodness-of-fit tests criteria with an implicit capability to manage false alarm through a reject class. Some experiments illustrate the range of performance achieved in terms of probability of correct identification. We end by addressing some principal extensions of our work.

2. OVERVIEW OF TARGET RECOGNITION

Thales is an important actor in Defence industry which proposes a great number of equipments and global solutions for weapon systems.

Its purpose is to improve its role and presence in the more and more sophisticated future weapon systems. Target recognition is one way to access to these future weapon systems.

This paper focuses on a technical solution for the identification task viewed as a necessary step to investigate the more generic problem of target recognition.

2.1 GENERAL METHODOLOGY

To date, considerable amounts of work have been carried out in the area of automated classification or identification, with some different issues being well understood.

The first issue is dimension reduction.

If we consider as input data an image chip of 60 by 60 pixels (inside which lies the potential target), then the intrinsic dimension of the input space is 3600. This could be easily seen by considering the image chip as a vector. Target images object live in a high dimensional space which is essentially an empty space.

The purpose of dimension reduction with the help of feature selection is, while reducing the intrinsic dimension, to project input data to the significant and non-empty part of the high dimensional space, corresponding to a low-dimensional space known as the feature space. Otherwise we will face the so-called curse of dimensionality problem [Ref 1]: to achieve good performances, the number of training images should be exponentially large in the number of features.

Petit-Frère, J.; Benoist, J.-C. (2005) A Data Analysis Approach of ATR from SAR Images. In *MMW Advanced Target Recognition and Identification Experiment* (pp. 12-1 – 12-10). Meeting Proceedings RTO-MP-SET-096, Paper 12. Neuilly-sur-Seine, France: RTO. Available from: http://www.rto.nato.int/abstracts.asp.

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The second issue is the feature selection in itself, i.e. finding some more or less “well-known” discriminating features.

The following list summarizes what seems to be the three major but unfortunately incompatible required qualities for those features :

1. stability or robustness against aspect angle variability but also against any classification noise. By classification noise we mean segmentation error of the target contribution pixels, but also the influence of an open door when it is expected closed for articulated objects.
2. discrimination capacity in order to be able to separate a T72 Main Battle Tank from a T62 Main Battle Tank in the identification problem.
3. exhaustiveness in order to achieve some optimality in terms of probability of correct classification : *Omitting a useful feature leads to a lost of performances*. On the other hand, there is the redundancy concept, which can be managed through features independence : *Adding a feature that is a function of other features is useless*.

Theoretically some trade-off have to be managed between these different qualities.

In practice the feature choice is rather often directed by physical interpretation. For instance, geometric features like length/width ratio are rather used than radiometric features like mean/standard deviation power ratio.

The last issue addresses the learning of the probability distributions of each class with the help of more or less complicated, parametric or non parametric, models. This is the achieved purpose of linear classifiers, generalised linear classifiers, but also in dual approach for neural networks and support vector machine methods [Ref 1].

As the feature choice is done manually, the same feature vector definition is used for all classes, giving the same probability distribution type. The consequence is that data reduction is class-independent.

2.2 TME METHODOLOGY

From the above general methodology, we retain that identification is carried out in a reduced dimension space.

Here we present the concrete Thales Missile Electronics methodology.

As inputs data, we use a set of high resolution SAR images, the MSTAR™ public released database, giving images of stationary vehicles in X-Band for every degree in azimuth with several values in elevation.

The data set is of very high quality and delivered with ground truth information.

The first step was the definition of a baseline algorithm with performance assessment. This baseline algorithm relies on a class-dependent model and uses features derived through data analysis tool in order to achieve the difficult (automatically) trade-off between the different required qualities. Furthermore a multiple goodness-of-fit tests criteria is applied in order to decide on target class with an implicit capability to manage false alarm through a reject class.

The second step is improvement of the baseline algorithm for acquiring sufficient robustness capability and the associated performance assessment.

The third step will be to produce a more operational identification method in introducing the use of synthetic data.

Thales currently pursues investigations in the two last steps, the following describes in details the first step.

3. IMAGE MODEL AND FEATURES EXTRACTION THROUGH DATA ANALYSIS TOOL

In this section, the image model used for each class is defined and its exploitation to derive the used features is described with an illustration derived from MSTAR™ database.

3.1 SAR IMAGE CONTEXT

SAR images of vehicles are characterised by a high variability signature, caused essentially by the return of a small number of objects on the vehicle.

A part of this variability is useless whilst another part is relevant to the identification problem.

As useless information, we have the target location, but also background echoes which implies to extract the significant signal i.e. target with optionally shadows pixels.

Sometimes levels of radar returns can be perceive as useless variability since they are relative to the radar specifications. In this case we can restrict our information to a binary information corresponding to target and shadows pixels locations. This is one way to perform normalisation of input data. Other normalisation techniques using radiometric information have also been tested.

As relevant but difficult information to manage we have the dependency of the target signature as a function of the target pose, accounting for the 3D target information through occluded parts.

In order to efficiently process this information we need to have a good idea how to predict with accuracy the expected signature with the help of a model.

As it seems unlikely to achieve this task over the 360 degrees in azimuth and 180 degrees in elevation, we propose to simplify the problem through a restriction on angular sectors. As consequence, the concept of sub-class defined as a target type and an angular sector is introduced for each target type and sector covering the 360 by 180 degrees. But even with this restriction, there is still a variability inside each sub-class which has to be taken into account.

3.2 IMAGE MODEL DEFINITION

The aim is to design local models in that they account for the signature behaviour of one target type inside an angular sector.

Images belonging to one given sub-class are distributed along a cloud of points in the high dimensional input space. As there is still variability inside the sub-class, the set of points is more or less extended.

The proposed image model here approximates the set of points by a linear manifold. That corresponds to the following linear representation :

$$s(x,y) = s_0(x,y) + \sum_{k=1}^{K} a_k \; s_k(x,y) + \varepsilon(x,y)$$

This above decomposition describes all potential images coming from the given sub-class and is obtained from principal component analysis with the help of a well descriptive database.

The $s_k(\;)$ functions correspond to eigenimages except for $s_0(\;)$ which is the statistical mean image of the set. These functions are linearly independent and form a vector base relative to the linear manifold.

The coefficient a_k varies from an image to another image inside the class. They express the variability inside the sub-class.

$\varepsilon(\;)$ corresponds to a residual controlled in power by the model order K : *a too high value of K could lead to overfitting while a too small value of K to underfitting*.

Having defined an image model for the given sub-class, the features are deduced as the invariant characteristics of the model, i.e. the eigenimages $s_k(\;)$.

This representation is justified if the power of the residual $\varepsilon(\;)$ is small regards the power of the image model of the sub-class. In that case we achieve an effective dimension reduction from the NxN pixels image chips to K+1 features corresponding to the functions $s_k(\;)$.

This systematic approach is applied for each sub-class, i.e. target type and angular sector, to derive its own image model.

3.3 FEATURE INTERPRETATION

The following figure illustrates the eigenimages obtained for a T62 with a angular sector of more than 45 degrees.

The target contribution and the shadow parts are separated for a better comparison, but they have to be considered “as a whole”.

Note that these eigenimages are obtained from aligned and normalised that is here binary images, but these result to grey-level images.

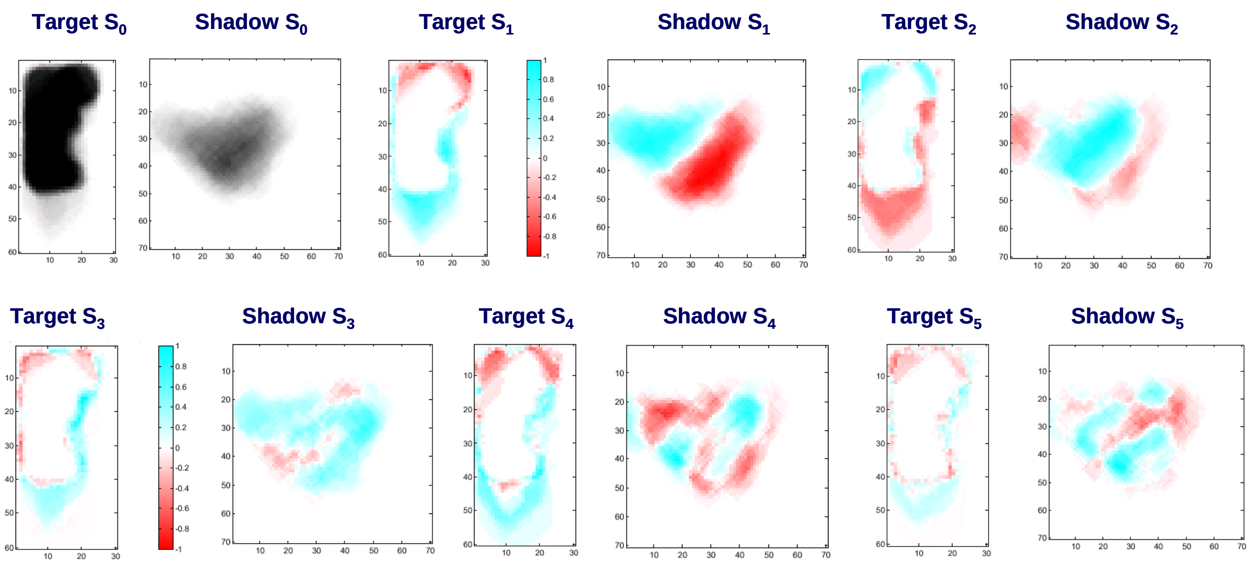


Figure 1 : Eigenimages derived for T62

The first feature is the statistical mean image.

Considering the mean shadow part, it is immediately apparent that the underlying data is much less consistent than for the target contribution. Shadow part is more sensitive to the change of orientation (that could be easily seen if we adopt a geometrical optical interpretation, even this is not the rigorous way).

At the bottom of the mean target part we have a brighter area corresponding to the T62 gun barrel. Most of the time the return from the gun barrel is not distinguishable from the clutter.

The following eigenimages illustrate the positive (blue) and negative (red) contributions of different areas inside the image model of the given sub-class. We recover from s_1 and s_2 the influence of the gun, but also some influences inside the shadow part. As a whole the eigenimages are orthogonal to each other in the sense of inner product defined in the high dimensional input space.

As the model order *K* increases, the different areas look more and more noisy.

The evaluation of the eigenimages for each target type with their different angular sectors is a part of the training phase. The other part is threshold determination used for each sub-class in multiple tests criteria described in the following section.

4. TEST PROCESSING

Once models have been characterized for each sub-class, i.e. eigenimages and model order are designed for each target type and angular sector pair, the test phase can be applied.

This phase is based on an accept/reject decision test of a given sub-class. The aim is to fit the observed image to the image model in order to decide if the image belongs to the given sub-class or not.

In statistics, there are well-known non parametric goodness of fit tests like chi squared or Kolmogorov-Smirnov tests [Ref. 2]. These tests are known to be very sensitive since they rely on a strict fit to the model. If the observed image doesn't follow precisely the model, the result of the test is a systematic reject decision.

Here we propose a less sensitive test which gives a better balance between the accept hypothesis *H*, i.e. "the observed image fit the model" and the reject or null hypothesis H_0. This is accomplished by a different specification of the reject hypothesis:

$$H: \ I(x,y) = s_O(x,y) + \sum_{k=1}^{K} a_k \ s_k(x,y) + w(x,y)$$

$$H_0 : I(x,y) = \varphi(x,y) + w(x,y)$$

Under *H*, the observed image $I(\ )$ follows the linear model described by the eigenimages relative to the given sub-class plus a noise contribution.

Under H_0, the observed image follows an unknown function $\varphi(\ )$, which can be any function which can not exactly match the sub-class image model; otherwise it is impossible to distinguish between *H* and H_0.

That gives rise to a particular but more complicated decision problem since the coefficient a_k and a function $\varphi(\ )$ are unknown.

To resolve this decision problem with unknown parameters, we use the invariance (equivariance) theory which postulates that there exists some optimal test in sense that it achieves the best performance whatever the values taken by the unknown parameters.

This kind of test exists if the decision problem exhibits some invariance properties regarding the action of data transformations. In this case, the theory says that this statistic test must exhibit the same invariance properties. The theory also indicates how to deduce the optimal test or so-called Uniformly Most Powerful test [Ref. 3].

That gives rise to evaluate the distance from the vectorial subspace described or embedded by the functions $s_k(\ )$ and compare it with a threshold defined by guaranteeing a minimal good detection probability.

So when the distance is smaller than the given threshold, the hypothesis *H* is true i.e. the observed image is declared coming from the associated sub-class.

In the ambiguous but practical case where more than one target type and sector are recognised, a final decision could consist in choosing the class giving the lowest distance.

In the particular case for which none of the sub-class is recognised, then the observed image is associated with the unknown class and the potential target is declared as coming from an unexpected target type.

These multiple tests criteria can efficiently cope with these different situations giving appropriate decision outputs.

5. PERFORMANCE

Some experiments to determine the performances have been carried out and are still under current investigations. A part of these experiments is reported here.

To illustrate the range of performance and compare different configurations, we show confusion matrix with an associated single figure of merit $Perf$ taking into account the use of a reject class.

We used MSTAR public released image database as inputs and performed training and test phases on it.

In a first experiment training and test image sets are common, the purpose was to assess the upper performance limit of our algorithm. In order to reduce the number of tests, we used a target orientation estimation procedure and compare each tested image to the angular sector eigenimages associated to its measured orientation. This specific implementation gives for a 3-class identification problem the confusion matrix table 1.

$Perf = 96.5\%$	**Brdm2_truck**	**Btr60_transport**	**T62_tank**	**Unknown**
Brdm2_truck : 15_deg	93.4	0.0	0.0	6.6
Btr60_transport : 15_deg	0.0	97.8	0.0	2.2
T62_tank : 15_deg	0.0	0.0	94.1	5.9

Table 1 : confusion matrix in 3-class identification problem

The reject cases are due to false and ambiguous orientation estimation when targets are closed to side-on (broadside flashes,…).

The following table 2 gives a comparison when we considered a 11-class identification problem. Note the implicit degradation of the figure of merit $Perf$ when we considered a large number of classes. In the two cases, ambiguities between useful classes are almost negligible.

$Perf = 90.1\%$	2s1	Bmp2	Brdm2	Btr60	Btr70	D7	Slicey	T62	T72	Zil131	Zsu23-4	Unkown
2s1_gun	92.0							0.4	0.4			7.3
Bmp2_tank	0.5	91.8		1.0					1.5	0.5		4.6
Brdm2_truck		0.4	91.2				0.7			0.4		7.3
Btr60_transport	0.5			93.4					1.6			4.4
Btr70_transport				0.5	90.8							8.7
D7_bulldozer	0.4					85.0				0.4		12.8
Slicey			2.2				95.6			1.1	1.5	1.1
T62_tank	0.4							89.7				9.9
T72_tank									90.8			9.2
Zil131_truck							0.4			80.7		19.0
Zsu23-4_gun						0.7					83.9	15.3

Table 2 : confusion matrix in 11-class identification problem

In a second experiment, training and test image sets are distinct, this corresponds to a more practical situation. The figure of merit $Perf$ in table 3 is lower by 8 percents than the upper limit achieved in the previous experiment for 3-class identification problem. The behaviour of the classifier is to choose rather the reject class than ambiguous class except for the 5 percents of misclassification of the btr60 in brdm2.

$Perf = 88\%$	Brdm2_truck	Btr60_transport	T62_tank	Unknown
Brdm2_truck : 15+17_deg	89.6		0.3	10.1
Btr60_transp : 15+17_deg	5.1	73.0		21.9
T62_tank : 15+17_deg			86.3	13.7

Table 3 : confusion matrix in 3-class identification problem

6. CONCLUSIONS

An identification procedure from SAR images has been presented. This procedure is based on a target image model derived from principal component analysis through the use of a detailed database.

The basic assumption is that a single model cannot summarize the image variability for all target poses, so several models are used for different angular sectors.

Training involves computing the mean and eigenimages then selecting model order and threshold for each target in each angular sector, while testing involves computing a distance (between the image and the model), then comparing it with the different thresholds.

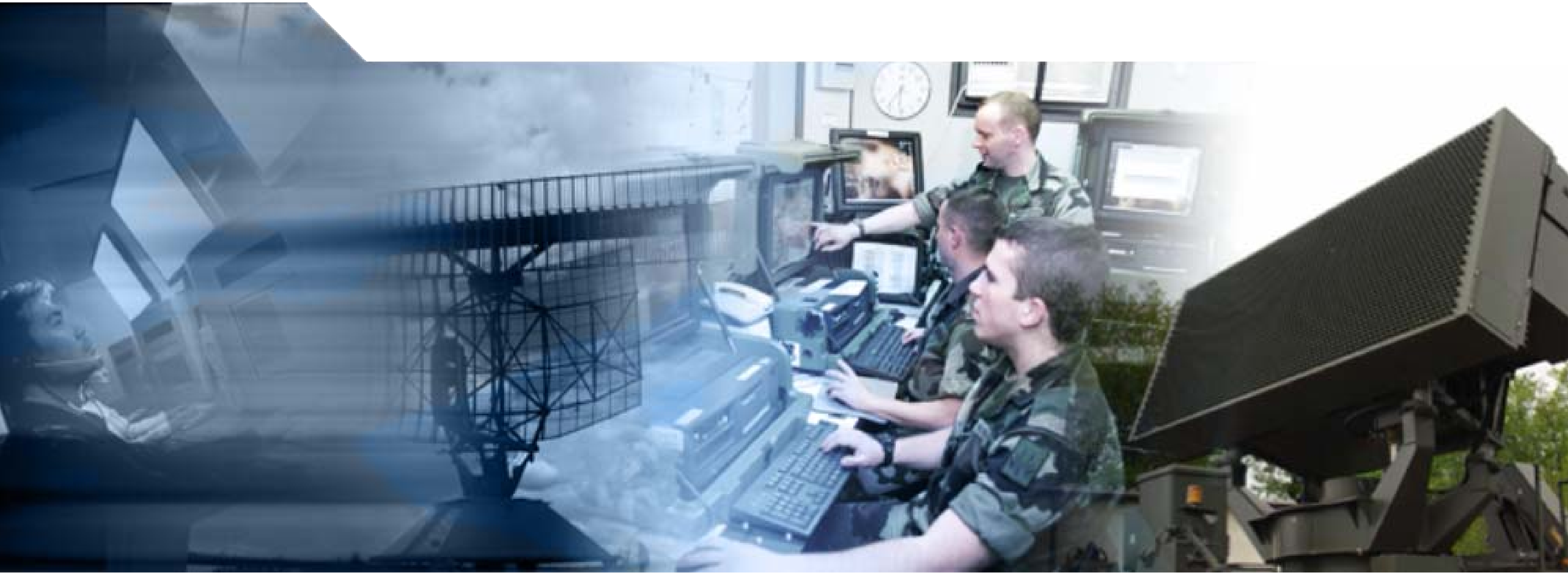
The results obtained from a first implementation of the procedure have shown a class of performance in terms of probability of correct identification around 90%.

We are currently investigating the issues of robustness to occlusions and articulations while keeping the previous target model. This approach implies a modification of the test processing through the evaluation of a new distance generalising the previous one.

Another extension is the use of synthetic data in substitution to real censored image database from a practical and economical point of view.

7. REFERENCES

1. Devroye L., Györfi L., Lugosi G. “A probabilistic theory of pattern recognition”, Springer-Verlag, New-York, 1996
2. Stuart A., Ord J.K. “Kendall’s advanced theory of statistics”, Oxford University Press, 5th Edition, Vol. 2, New-York, 1991
3. Lehman E.L. “Testing statistical hypotheses”, Chapman & Hall, 2nd Edition, 1994



A Data Analysis Approach of ATR from SAR Images and Data Inputs Requirements

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- Target recognition overview
- TME's methodology
- Image model and feature extraction through data analysis
- Processing of classification
- Experiments
- Generalised processing
- Conclusion

- Operational Requirements
  - select the target in a set of targets of interest, for example tank or vehicles in a complex environment

Generic classification problem

- Technical Approach
  - **Paradox**, the problem is simplified using a SAR image by addressing the target identity : T72 MBT compared to a T62 MBT

Identification problem

Identification is not an end in itself, but a necessary step to resolve the generic classification problem

- Dimension reduction : *from Input Space to Feature Space*

  For instance : $D_{input} = 3600$ *to* $D_{feature} = 5$

  Images of target live in high-dimensional but empty space

- Extraction of « well-known » discriminating features

  For instance : *CVAR, WFR, Area, Length, polarimetric ratios*

  - Stability/robustness wrt the unknown target pose and classification noise (= segmentation error, articulation,…)
  - Discrimination capability
  - Exhaustiveness in order to achieve optimal performance in terms of probability of correct classification (and redundancy, independence)

  The feature choice is more directed by physical interpretation

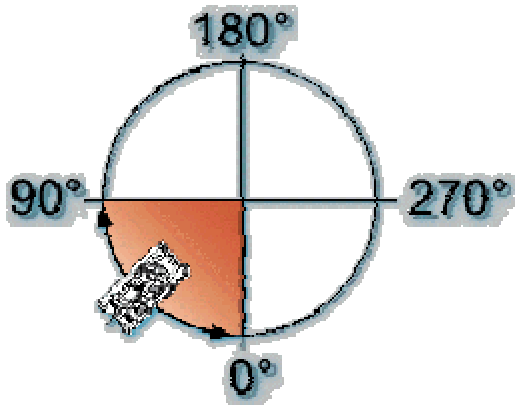
- Learning of the probability laws for each class

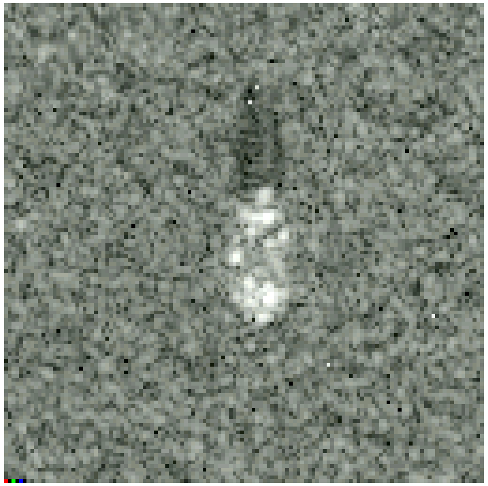
  The data reduction is often class-independent

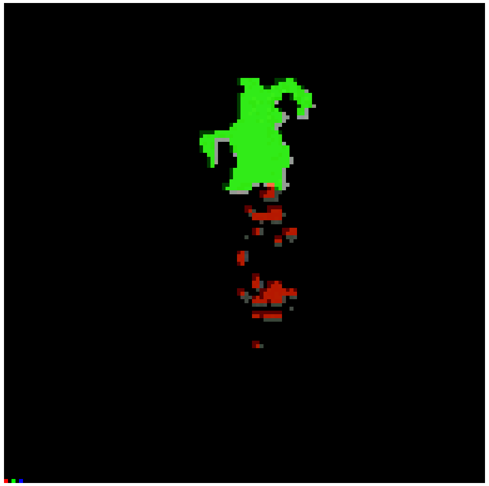
Classification is carried out in a reduced dimension space

- Input data : *MSTAR public released database*
  - Set of high resolution SAR measured images (every degree in az, several values in el, in X-Band) of a variety of stationary targets
  - No artefact, low noise and ground truth (actual target pose)
- First step : definition of a baseline algorithm and its performance assessment,
  - A class-dependant model
  - Features derived through **data analysis**
- Second step : algorithm robustness improvement and performance assessment
  - Robustness in terms of camouflage, articulation, …
- Third step : towards an operational method through the use of synthetic data

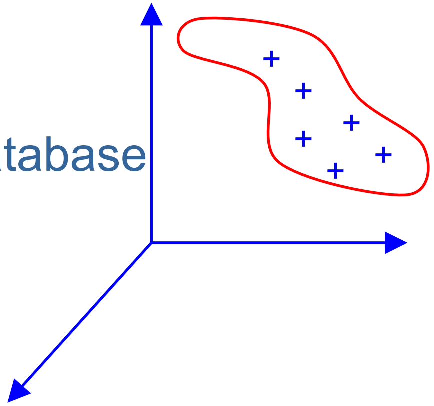
- Experiment knowledge : a high variability signature
  - Need to extract the useful signal : target (+ shadow) pixels
  - Need to separate in sub-classes (poses) : angular sector
  - Variability inside the sub-class







- Linear representation of data (images)
  - Principal Component Analysis (PCA)
    obtained from realistic, complete and noiseless Database

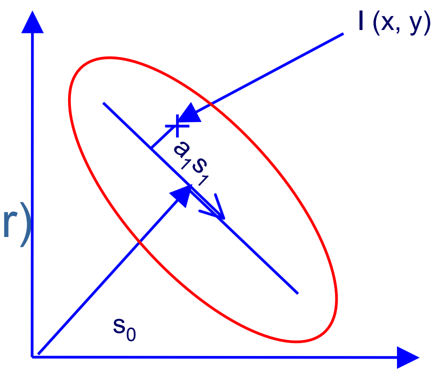


$$s(x,y) = s_0(x,y) + \sum_{k=1}^{K} a_k \; s_k(x,y) + \varepsilon(x,y)$$

- $s_k(.,.)$ are the invariant features of the class
- $\{a_k\}$ express the intra-class variability
- $K \leq 5$ controls the residual power (model order)

  The Model is justified when :

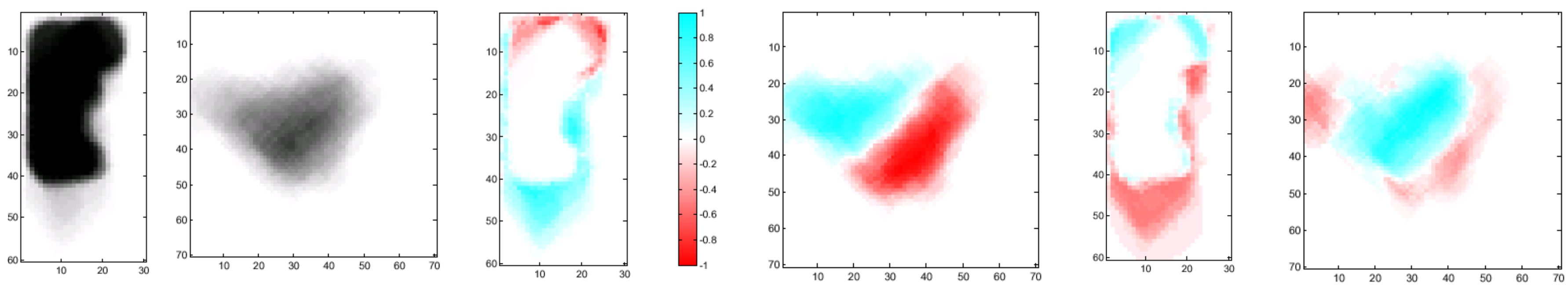
  $\|\varepsilon(,)\|_2^2 << \|s(,)\|_2^2$ energetic criterion



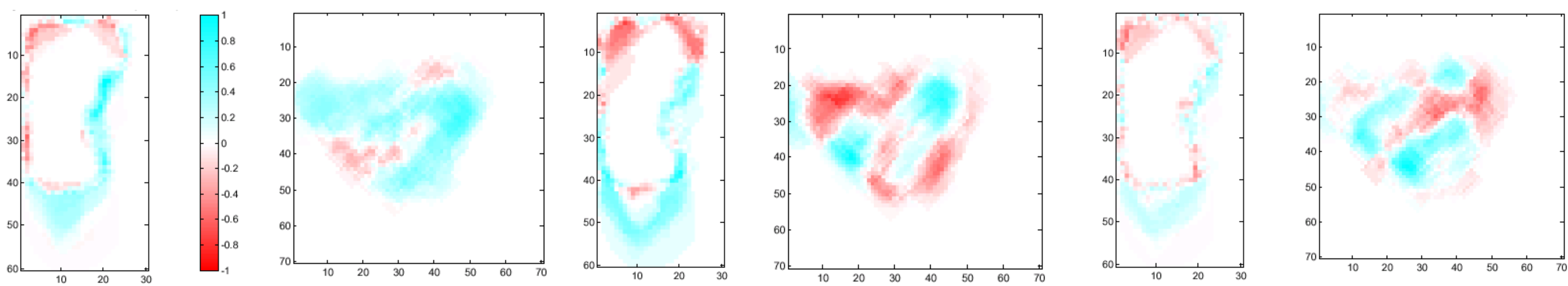
Modelling adapted to each class

- Linear representation of data (images)
  - T62 principal components

Target S_0 Shadow S_0 Target S_1 Shadow S_1 Target S_2 Shadow S_2



Target S_3 Shadow S_3 Target S_4 Shadow S_4 Target S_5 Shadow S_5



- Accept/Reject decision of a sub-class
  = "fit" between observations and model

- Desensitization of a classical "goodness of fit" test

- Decision problem with two hypothesis

$$H : I(x,y) = s_0(x,y) + \sum_{k=1}^{K} a_k \, s_k(x,y) + w(x,y)$$

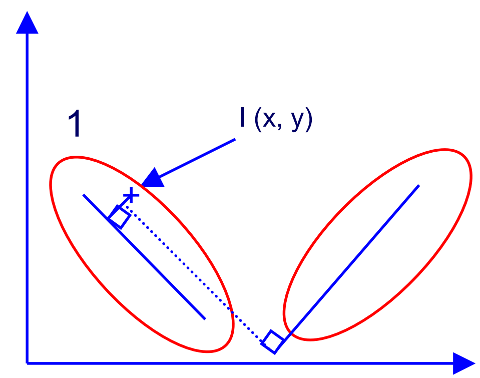
$$H_0 : I(x,y) = \varphi(x,y) + w(x,y)$$

$(a_k), \varphi(.,.)$ are unknown

Processing (2)

- UMP Test (invariant optimal)

$$\nu \ \underset{H}{\overset{H_0}{\gtrless}} \ \text{THRESHOLD}$$



Distance from
the vectorial sub-space
described by the functions $s_k(.)$

introduction of reject or unknown class for data which do not fit the multiple threshold criteria

- Classification of targets in training set : 3 v 11 classes

$$Perf = 96.5\%$$

	Brdm2_truck	Btr60_transport	T62_tank	Unknown
Brdm2_truck : 15_deg	93.4	0.0	0.0	6.6
Btr60_transport : 15_deg	0.0	97.8	0.0	2.2
T62_tank : 15_deg	0.0	0.0	94.1	5.9

$$Perf = 90.1\%$$

	2s1	Bmp2	Brdm2	Btr60	Btr70	D7	Slicey	T62	T72	Zil131	Zsu23-4	Unkown
2s1_gun	92.0							0.4	0.4			7.3
Bmp2_tank	0.5	91.8		1.0					1.5	0.5		4.6
Brdm2_truck		0.4	91.2				0.7			0.4		7.3
Btr60_transport	0.5			93.4					1.6			4.4
Btr70_transport				0.5	90.8							8.7
D7_bulldozer	0.4					85.0				0.4		12.8
Slicey			2.2				95.6			1.1	1.5	1.1
T62_tank	0.4							89.7				9.9
T72_tank									90.8			9.2
Zil131_truck							0.4			80.7		19.0
Zsu23-4_gun						0.7					83.9	15.3

- Classification of targets similar to training set

$$Perf = 96.5\%$$

	Brdm2_truck	Btr60_transport	T62_tank	Unknown
Brdm2_truck : 15_deg	93.4	0.0	0.0	6.6
Btr60_transport : 15_deg	0.0	97.8	0.0	2.2
T62_tank : 15_deg	0.0	0.0	94.1	5.9

Target and grazing angle unchanged

$$Perf = 88\%$$

	Brdm2_truck	Btr60_transport	T62_tank	Unknown
Brdm2_truck : 15+17_deg	89.6		0.3	10.1
Btr60_transp : 15+17_deg	5.1	73.0		21.9
T62_tank : 15+17_deg			86.3	13.7

Target unchanged, grazing angle changed

- Robustness at accept/reject decision level
  - Missing parts : occlusions, obstacles
  - Additional parts : camouflage, decoy, carried equipments,
  - Articulation variation
  - Error in segmentation : non-detection, false-alarm
- Decision between two hypothesis :

$$H : I(x,y) = (1-\delta(x,y))\left(s_0(x,y) + \sum_{k=1}^{K} a_k\ s_k(x,y) \right)$$

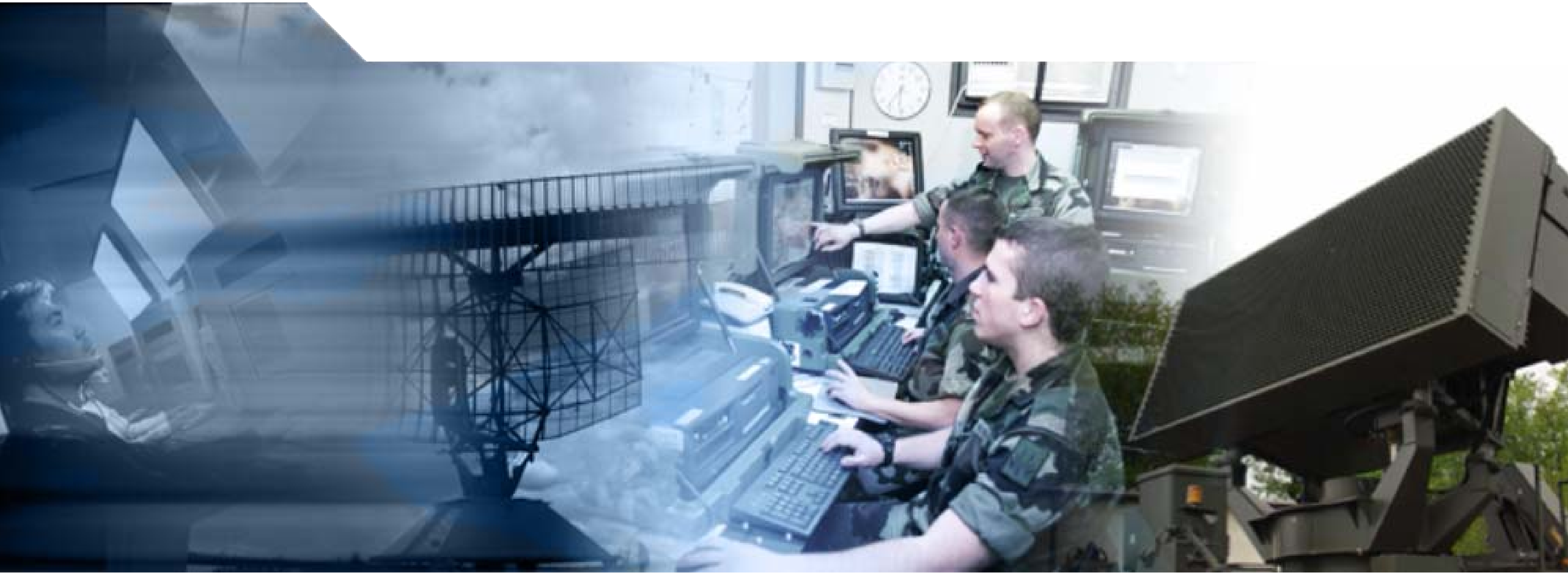
$$+\delta(x,y)\xi(x,y) + w(x,y)$$

$$H_0 : I(x,y) = \varphi(x,y) + w(x,y)$$

with additional unknowns $\xi(.,.)\,;\,\delta(x,y) = \begin{vmatrix} 1\ with\ \Pr ob = q \\ 0 \qquad\qquad 1-q \end{vmatrix}$

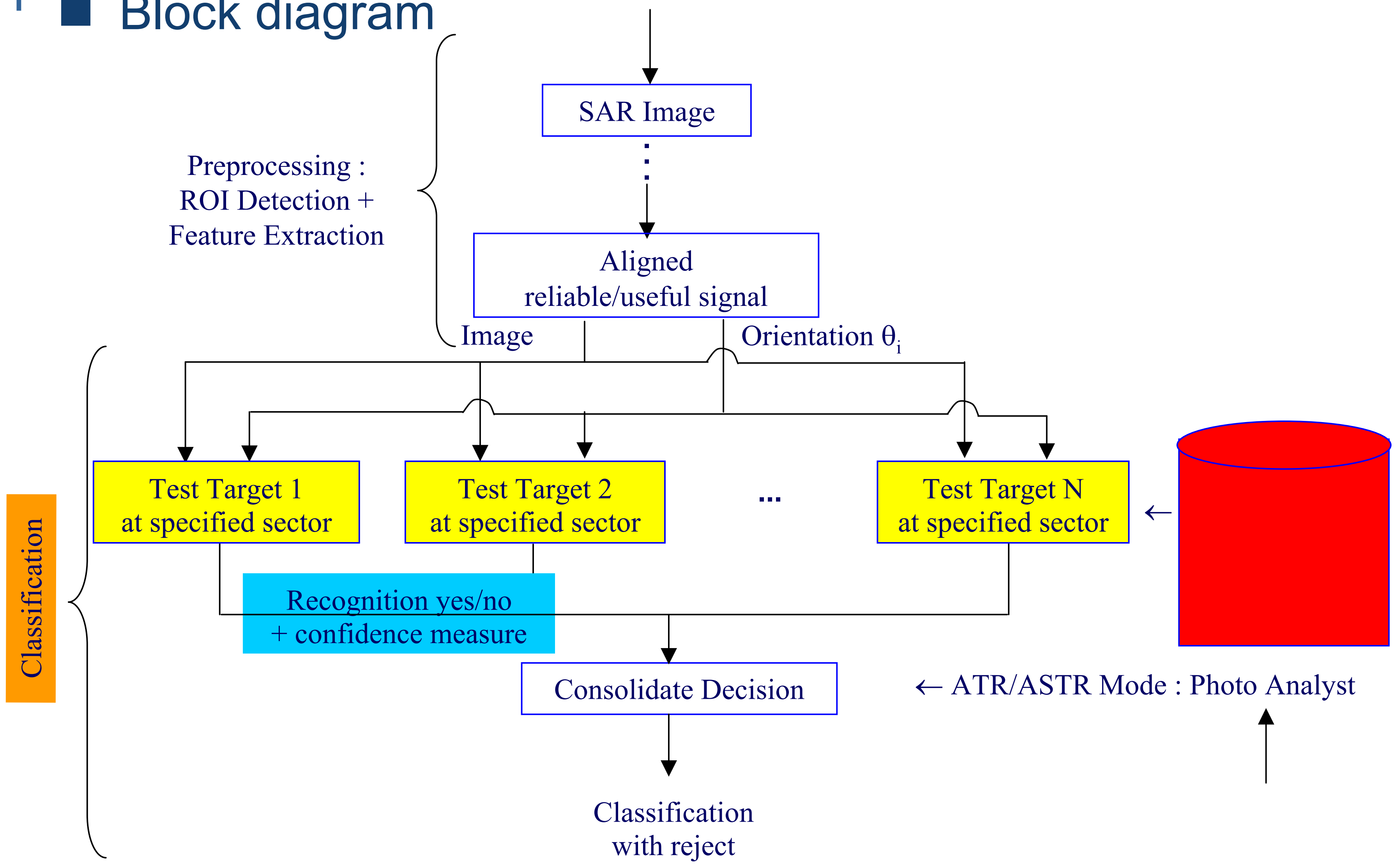
- Test : compare a new distance to a threshold

- Remarks concerning this kind of classification
  - Adapted data reduction for each class
  - Explicit processing for the “reject” class
  - Taking into account the intra-class variability
  - Measurement of the class model order validity
  - New class introduction capabilities without retraining previous classes



Thank you for your attention

- Block diagram



- First stage towards a complete demonstrator
- Use of geometrical model in order to built the database